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DIABETIC RETINOPATHY BINARY CLASSIFIER

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Abstract : In 2010, the International Diabetes Federation (IDF) stated that around 50.8 million individuals in India were affected by diabetes, and this figure is projected to reach 87.0 million by 2030. Diabetic Retinopathy is a prominent worry when it comes to Type II diabetes complications. It frequently results in loss of vision, especially in people between 20 and 64 years old. Over a period of time, Diabetic Retinopathy interferes with the regular drainage of fluid from the eye, causing a rise in pressure within the eyeball and possibly harming the nerves, ultimately resulting in the development of glaucoma. Prompt detection and intervention for Diabetic Retinopathy are essential in order to prevent the loss of vision. Yet, diagnosing manually by ophthalmologists is time-consuming, demanding in labor, and expensive, while also posing a risk of misdiagnosis without the use of computer-aided diagnostic systems. Lately, Deep Learning has become a potent tool, especially in the field of medical image analysis and classification. This research focuses on the difficulty of forecasting diabetic retinopathy to avoid additional issues. A model was created utilising the compact MobileNet architecture and was trained on retinal fundus pictures from the Aptos 2019 competition dataset. The suggested model attained an impressive 96% accuracy, along with precision, recall, and f-1 scores of 0.95, 0.98, and 0.97 respectively. These findings suggest the possibility of using this model in clinical settings. Nevertheless, it is crucial to emphasise that the purpose of this project is not to supplant ophthalmologists but rather to support them in detecting diabetic retinopathy complications at an early stage.

***IndexTerms* - Diabetic Retinopathy, Convolutional neural network, Deep learning, MobileNet Architecture**

I. INTRODUCTION

Diabetes provides a rich environment for implementing deep learning concepts [1]. Many researchers are working on forecasting diabetes and the related complications. While there are numerous apps that support research on the illness and its intricacies, they all come with their own advantages and disadvantages. As stated in [2], Indians have a higher risk of diabetes because of factors such as their lifestyle, eating habits, and lack of exercise. Diabetic Retinopathy (DR), a significant complication of diabetes, impacts the human eye. DR happens when the blood vessels in the retina, the light-sensitive layer in the back of the eye, are harmed, resulting in swelling and leakage of fluids and blood. A primary reason for vision loss in people aged 20 to 64 is this condition [3]. Diabetes and its complications are increasingly common worldwide. It is projected that the number of people with diabetes will increase to 438 million by 2025 and could potentially rise to 700 million by 2045 [4]. In India, despite the presence of approximately 127,000 ophthalmologists, almost 45% of patients go blind before being diagnosed because of the lack of screening equipment in rural areas. At present, the diagnosis of DR is a lengthy procedure, involving skilled physicians examining colour retinal images and categorising the severity into four groups [5]. This technique, although efficient, requires about 48 hours to show results, posing a challenge for timely intervention. Yet, as diabetes becomes more common, there is a growing demand for improved diagnostic systems.In order to tackle this problem, Google's research team partnered with EyePACS in the United States and three eye hospitals in India [6]. They aimed to create sophisticated software using deep learning technology to automatically detect DR. Partnership between diabetes specialists and eye doctors is on the rise, despite a lack of ophthalmologists skilled in diagnosing and treating DR. In countries with strong economies such as the USA, many diabetic individuals have not had an eye check-up and those who have may not get thorough evaluations. Examining fundus images is a frequent technique used to identify diabetic eye conditions, such as DR, which advances in four stages [7]. During its later phase, there is an increase in abnormal blood vessel growth on the surface of the retina, resulting in scarring and loss of cells. Certain research projects have investigated the application of Mobile-Based AI in detecting DR. Utilising models such as MobileNet for accurate classification into two categories [8]. In contrast to bulky and demanding models, MobileNet is a lightweight design ideal for mobile gadgets with restricted memory and computational capabilities. This method shows potential for improving the detection of DR and increasing diabetic patients' access to timely care.

II. LITERATURE REVIEW

Recent studies have demonstrated an increasing focus on creating smaller and more effective networks. Several methods have been investigated, ranging from compressing already trained models to training smaller network models. Certain researchers have utilised fuzzy inference systems to evaluate the likelihood of severe diabetes complications. An example is when Andrew G. Howard and colleagues presented a model that is effective in creating neural networks that are lightweight, which can be advantageous for tasks such as fine-grained classification and object detection using small, low-latency models. Yuchen Wu and colleagues concentrated on categorising diabetic retinopathy using advanced models like VGG19, InceptionV3, and ResNet, implementing transfer learning on Kaggle datasets and reaching a test accuracy of 60%, surpassing models trained from the beginning. In the meantime, Yunlei Sun and colleagues created a diabetic retinopathy detection model by examining electronic health records from 201 hospitals using five different algorithms, with the Random Forest model achieving a 92% accuracy rate. Y. Sun introduced a mixed CNN model with BN layers to detect diabetic retinopathy, obtaining notable training and test accuracies of 99.85% and 97.56%, respectively, on one-dimensional datasets. Early detection of diabetic retinopathy was introduced by Lam C. et al. using convolutional neural networks on colour fundus images, utilising transfer learning with models such as GoogLeNet, AlexNet, and ImageNet, and obtaining test accuracies between 52.2% and 74.5%. Moreover, Carson Lam and colleagues introduced a diabetic retinopathy detection approach based on deep learning, achieving a validation sensitivity of 95%, with a significant highlight being the use of limited adaptive histogram equalisation preprocessing.

III. PROPOSED SYSTEM

1. DATASET.

Images of the fundus obtained from Kaggle were utilised in this research. The APTOS dataset was used to train and test the MobileNet model for the 2019 blindness detection competition. The dataset contains 3662 high-quality retina images, including 1800 images showing diabetic retinopathy and 1800 without the condition. The dataset contains classes from 0 to 4, where 0 represents no diabetic retinopathy, 1 represents mild DR (Stage 1), 2 represents moderate DR (Stage 2), 3 represents severe DR (Stage 3), and 4 represents proliferative DR (Stage 4), which may result in significant vision loss. 650 images from the dataset were set aside for validation purposes. At first, the dataset was converted to binary form to have an equal number of diseased and non-diseased cases, reducing bias. Preprocessing required resizing images to (224,224,3) pixels and normalisation for data variance reduction. In order to ensure clearness, vector graphics were chosen instead of rasterized images for diagrams and schemas. Line sketches were guaranteed to have unbroken lines of uniform width and a resolution of a minimum of 800 dpi. Text inside figures remained readable, with font sizes no less than 6 pt (~2 mm character height). Figures were assigned numbers, while captions were placed underneath them to ensure easy identification.

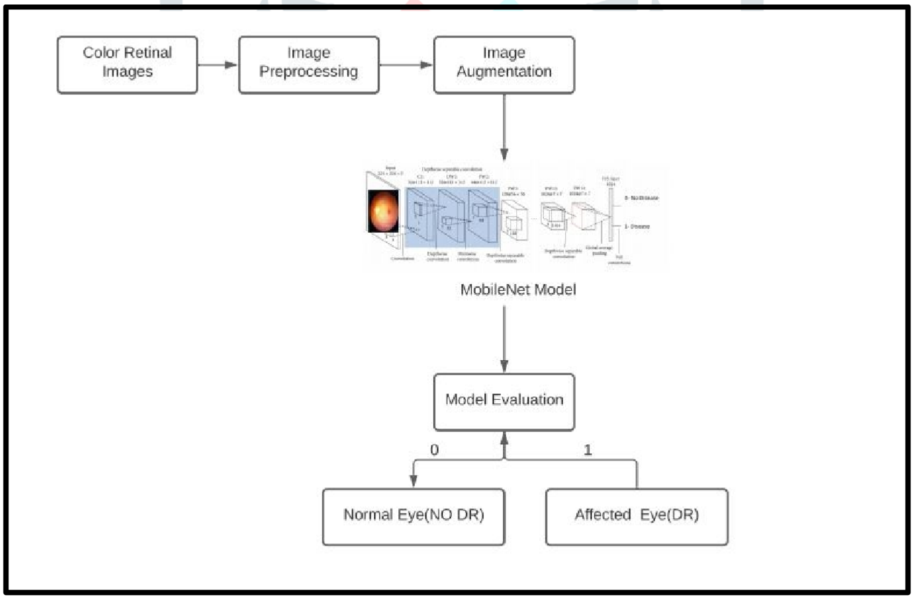

Fig no. 1 Block Diagram of the proposed system

2. PREPROCESSING.

During preprocessing, the input images in the dataset are adjusted in size because of their large resolution, leading to a considerable increase in memory usage. Changing the dimensions of the images to 224x224 pixels is performed in order to prepare them for inputting into the neural network, as utilising the original high-resolution images could lead to a substantial increase in computation time. Normalisation of images is then done to decrease variability in data points. After normalisation, the dataset is transformed into binary form. Adding a binary target column to the train.csv file involves assigning images with a diagnosis value of 0 a label of 0, while images with diagnosis values 1 to 4 are labelled as 1 in the binary target column. Up-sampling and down-sampling techniques are used to balance the binary dataset by ensuring an equal number of images for both classes (0 and 1). Next, the data is separated into three sections: training data, testing data, and validation data subsets. The validation set is utilised while training to observe and address overfitting.

3. METHODOLOGY.

In our proposed system, we have developed a model using MobileNet Architecture. Unlike other models like Inception, MobileNets require less regularisation and data augmentation. Additionally, the network has a smaller input size. The output of the neural network is class labelled as either DR (Diabetic Retinopathy) or no DR. The architecture is trained and tested using Python with the TensorFlow library installed. MobileNet is known for its lightweight design, leveraging depthwise separable convolutions. This means it performs a single convolution on each colour channel separately, rather than combining all channels, resulting in efficient filtering of input channels and high performance. We trained the MobileNet Architecture using the APTOS dataset, which rates each image based on the severity of diabetes on a scale of 0 to 4. These images are processed and then categorised into binary labels. The dataset consists of 3662 images, with 650 images used for validation. During preprocessing, the images are resized to (224, 224, 3) pixels and passed through a specially designed preprocessing method for MobileNet architecture. For model building, we remove the top 6 layers of MobileNet and attach a Dropout layer and a Dense layer with "SoftMax" activation. The first 23 layers are set as untrainable, while the remaining layers, along with the 2 added layers, are trainable. We employ various callbacks during training, including Early Stopping, ReduceLrOnPlateau, checkpoint, and csv_logger. The Adam optimizer is used, with the loss function set as categorical_crossentropy and the metric as categorical_accuracy.

IV. ADVANTAGES

1. Detection at an early stage of Diabetic Retinopathy (DR) is the goal of the project, which utilises Convolutional Neural Networks (CNNs) with MobileNet Architecture. Detecting DR early is important in starting interventions promptly to stop the advancement of the disease and reduce the chances of losing vision.

2. Automation: The suggested method automates the identification of DR from fundus images. This automation decreases dependence on manual diagnosis, which is both time-consuming and labour-intensive, by utilising machine learning algorithms to efficiently analyse images.

3. Efficiency was the main reason for selecting the MobileNet Architecture, as it is efficient in terms of computational resources and memory needs. This enables the model to be used on platforms with limited resources, like mobile devices or low-power computing environments, while maintaining performance.

4. Utilising transfer learning techniques, the project leverages the knowledge of pre-trained models and applies it to the particular task of DR detection. This method speeds up the training of the model and enhances its capacity to generalise to unfamiliar data.

5. The project uses data augmentation and normalisation methods to improve the model's resilience. These methods help address problems caused by fluctuations in fundus image quality and guarantee that the model can effectively acquire distinguishing features from the data.

6. Possibilities for Future Improvements: The project identifies various opportunities for future exploration and advancement, including enhancing the model's effectiveness with real-world data, equalising the training data sets, and categorising various forms of DR. These improvements could enhance the model's precision and effectiveness in clinical environments.

In general, the project presents a hopeful method for detecting DR, which could greatly benefit healthcare by aiding in the early detection and treatment of diabetic patients.

V. APPLICATIONS

1. Clinical Diagnosis Support: The newly created model offers healthcare professionals automated help in diagnosing Diabetic Retinopathy (DR), serving as a useful tool. Through the examination of fundus images, the model is able to assist clinicians in promptly and precisely recognizing patients who may be susceptible to developing DR or who need additional assessment and care.

2. In areas where there is a lack of specialised eye care facilities, the project's automated DR detection system can be used in telemedicine applications for remote screening. Patients have the ability to remotely upload fundus images for assessment of signs of DR by the system, which allows for early intervention and decreases strain on healthcare infrastructure.

3. Population Screening Programs: The automated DR detection system of the project can be incorporated into population screening programs targeting individuals with undiagnosed diabetes or DR. By efficiently analysing large amounts of fundus images, the system can assist in screening at-risk populations and identifying those who require further examination by healthcare providers.

4. Health Solutions: With the effectiveness of MobileNet Architecture and its suitability for use on mobile devices, the project's DR detection system has the potential to be integrated into mobile health apps. Patients are able to take images of their fundus using their smartphones, with the model analysing them to give immediate feedback on their eye health.

4. Research and Clinical Trials: The advanced model can also be employed in research investigations and medical trials. Researchers can use the model to examine extensive fundus image datasets, detect patterns and trends, and assess the impact of new treatments or interventions on DR.

5. Education and Training: The automated system for detecting DR in the project can be integrated into educational programs for ophthalmologists, optometrists, and other healthcare professionals. The system improves learners' diagnostic skills and understanding of DR pathology and management by allowing them to work with actual clinical data.

VI. RESULT

Our paper suggests a deep learning model for identifying Diabetic Retinopathy with Convolutional Neural Networks (CNNs), specifically using MobileNets architecture with depth-wise separable convolutions. During 100 epochs of training, the model achieved its best performance at the 24th epoch with an f1-score of 0.96. Accuracy is defined as the percentage of correct classifications, achieving a total accuracy of 0.96 and showing a significant finding in the confusion matrix, which outlines the model's performance through True Positives, True Negatives, False Positives, and False Negatives. The Quadratic Weighted Kappa measures how closely actual and predicted values match, resulting in a score of 0.93, showing strong agreement. Moreover, we assess alternative performance metrics like precision, recall, and f1-score for comparison. Precision evaluates the percentage of correct positive predictions, recall calculates the ratio of correct positive predictions to the total of true positives and false negatives, and f1-score is the balanced combination of precision and recall, providing a fair evaluation of model performance. The MobileNet structure, which incorporates shallow layers in the CNN, employs compact convolutional filters, leading to improved classification outcomes. Yet, this method could potentially lower the effectiveness of the model and create real-world obstacles. The diagram shows the model's training and validation loss, along with its training and validation accuracy, to give an understanding of its training progress and performance assessment.

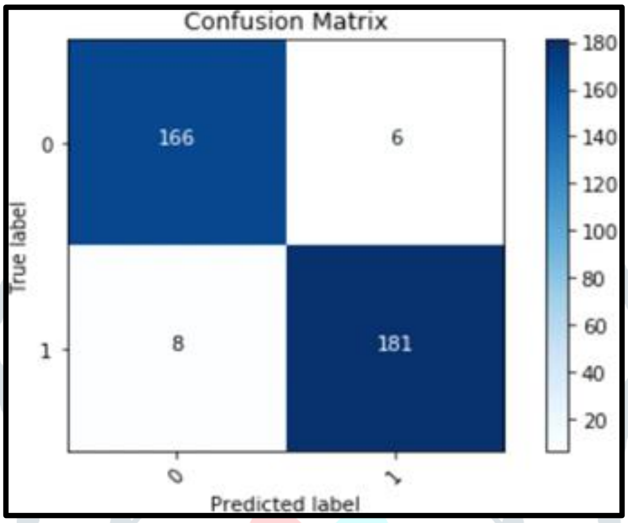

Fig no. 2 Confusion Matrix.

	precision	recall	f1-score	support
0	0.95	0.97	0.96	172
1	0.97	0.96	0.96	189
accuracy			0.96	361
macro avg	0.96	0.96	0.96	361
weighted avg	0.96	0.96	0.96	361

Fig no. 3 Performance Analysis.

VII.CONCLUSION

In conclusion, Diabetes is increasingly prevalent, with diabetic patients facing a 30% risk of developing Diabetic Retinopathy (DR). DR progresses through stages, potentially leading to blindness if not detected early. Manual diagnosis is laborious and requires expertise. This paper proposes using Convolutional Neural Networks (CNNs) with MobileNet Architecture for DR detection, leveraging transfer learning to classify fundus images and streamline feature extraction. Data normalisation and augmentation compensate for image defects, alongside model selection and parameter training. Despite compression and acceleration potentially reducing classification accuracy, integrating dense blocks in MobileNet enhances performance. Future directions include refining model performance and accuracy by training with real hospital datasets, ensuring balanced classification representation, utilising high-resolution retinal images, and classifying different DR types.

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REFERENCES

[1] Sheikh, Sarah, and Uvais Qidwai. "Using MobileNetV2 to Classify the Severity of Diabetic Retinopathy." International Journal of Simulation--Systems, Science & Technology 21.2 (2020).

[2] Patel, Sanskruti. "Diabetic retinopathy detection and classification using pre-trained convolutional neural networks." International Journal on Emerging Technologies 11.3 (2020): 1082-1087.

[3] Gao, Jiaxi, Cyril Leung, and Chunyan Miao. "Diabetic retinopathy classification using an efficient convolutional neural network." 2019 IEEE International Conference on Agents (ICA). IEEE, 2019.

[4] Suriyal, Shorav, Christopher Druzgalski, and Kumar Gautam. "Mobile assisted diabetic retinopathy detection using deep neural network." 2018 Global Medical Engineering Physics Exchanges/Pan American Health Care Exchanges (GMEPE/PAHCE). IEEE, 2018.

[5] Verma, Kanika, Prakash Deep, and A. G. Ramakrishnan. "Detection and classification of diabetic retinopathy using retinal images." 2011 Annual IEEE India Conference. IEEE, 2011.

[6] Azar, Ahmad Taher, and Valentina E. Balas. "Classification and detection of diabetic retinopathy." Advances in Intelligent Analysis of Medical Data and Decision Support Systems. Springer, Heidelberg, 2013. 135-145.

[7] Shorav Suriyal; Christopher Druzgalski; Kumar Gautam,"Mobile Assisted Diabetic Retinopathy Detection using Deep Neural Network"

[8] APTOS Dataset : https://www.kaggle.com/c/aptos2019-blindness-detection

[9] "Kaggle Diabetic Retinopathy Detection," https://www.kaggle.com/c/ diabetic- retinopathy-detection/data, accessed: 2018-04-30.

[10] Tensorflow-for-poets-2.(2017).https://codelabs.developers.google.com/codelabs/tensorflow-for-poets-2/#3